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ELECTRICITY DEMAND FORECASTING IN SMART GRIDS BASED ON MACHINE LEARNING MODELS

The paper addresses the urgent problem of high-precision short-term electricity demand forecasting within modern intelligent power systems (Smart Grids). The transformation of the energy sector, driven by the decentralization of generation and the massive integration of renewable energy sources, necessitates new approaches to processing large volumes of high-frequency data. The inefficiency of traditional statistical models, such as ARIMA, for analyzing complex non-linear dependencies in dynamic networks is substantiated. The Long Short-Term Memory (LSTM) neural network model was chosen as the primary research method, as it effectively addresses the vanishing gradient problem and captures long-term temporal dependencies. The model integrates both primary time series of historical demand and exogenous factors, specifically weather conditions and calendar events. Experimental studies were conducted using high-resolution data (5-minute intervals). Modeling results demonstrated a significant advantage of LSTM over ARIMA and XGBoost models. The use of LSTM allowed for a 20–50% reduction in forecasting errors (RMSE and MAE metrics) compared to traditional methods, achieving values of MAE of 7.8 kW and RMSE of 10.5 kW. The practical value of the results lies in the potential to minimize operating costs, optimize the performance of energy storage systems, and enhance the overall stability of Smart Grids.

Keywords: *energy efficiency, demand forecasting, smart grid, machine learning, LSTM, recurrent neural networks.*

Introduction. Modern power systems are undergoing a significant transformation, moving towards the Smart Grid model. This is driven by the decentralization of generation, the massive integration of renewable energy sources (RES), and the need to process large volumes of high-frequency data (Big Data).

In the context of Smart Grids, the forecasting target is increasingly not just total consumption, but the so-called "net demand," which is formed as the difference between the facility's total energy requirement and the energy generated by its local renewable sources (e.g., solar panels). This transforms consumers into active grid participants (prosumers) and makes the grid consumption profile highly stochastic. It is precisely this volatility, driven by the impact of weather conditions on local generation, that explains the inefficiency of traditional linear models and necessitates the application of recurrent neural networks.

Inaccurate demand forecasting in such dynamic conditions leads to significant economic losses, increased operating costs, and risks to system instability. Traditional statistical models (e.g., ARIMA [1]) are ineffective for analyzing the complex, non-linear dependencies that arise in modern Smart Grids [2]. Consequently, there is a need to develop and investigate advanced methods, particularly machine learning (ML), to significantly improve the accuracy of short-term demand forecasting.

Recent scientific research is actively shifting from traditional statistical methods to the use of complex ML architectures. Key areas include:

–Studies emphasize the use of Recurrent Neural Networks (RNN) and their modifications, specifically Long Short-Term Memory (LSTM). These models have shown high efficiency in capturing long-term temporal dependencies in energy consumption time series [3, 4].

–The use of Gradient Boosting (XGBoost) is widespread, especially for the effective integration of heterogeneous external features (weather, calendar events) [5, 6].

–Combining LSTM for temporal dependencies with, for example, XGBoost for non-linear features, which increases the overall robustness and accuracy of the forecast [7, 8].

Despite this progress, existing models have certain limitations. Most studies work with hourly or daily data. The problem of accurate forecasting at 5–15 minute intervals remains relevant, as it is critical for operational management. Additionally, there is insufficient integration of the impact of unpredictable RES generation as a dynamic factor, which complicates net demand forecasting [9, 10, 11].

Scientific Contribution. Unlike existing studies that primarily utilize LSTM for hourly or daily forecasting, the authors' contribution in this work lies in adapting the machine learning model for ultra-short-term forecasting using high-frequency data (5-minute intervals). This approach enables the identification of consumption micro-trends that are otherwise obscured by hourly averaging, which is critical for the real-time operational management of hybrid microgrids and energy storage systems.

Research Objective. The objective of this work is to develop and experimentally validate the effectiveness of the Long Short-Term Memory (LSTM) model for high-precision short-term electricity demand forecasting in Smart Grids, utilizing high-frequency data and integrating key external factors.

Main Material. The object of the study is the aggregated load of a local microgrid (e.g., an infrastructure facility or a group of consumers) with a baseline power range of 800 to 1300 kW. The LSTM model is a type of Recurrent Neural Network (RNN) specifically designed to work with time series and to overcome the vanishing gradient problem inherent in conventional RNNs when processing long sequences [3, 12].

The LSTM model employs special internal structures called memory cells, which allow it to selectively store, read, and discard information over extended periods. This is ideally suited for electricity demand forecasting, where current consumption depends on factors that were active days, weeks, or even months ago.

Each LSTM cell has three main gates that control the flow of information:

Forget Gate (f_t) – determines which part of the information from the previous cell state (C_{t-1}) should be forgotten or discarded.

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right)$$

where x_t – input data at time t (e.g., current temperature, demand); h_{t-1} – hidden state (output) from the previous time step t-1; W_f, b_f – weight matrix and bias vector for the forget gate; σ – sigmoid activation function (outputs values from 0 to 1), where 1 means "keep entirely" and 0 means "forget entirely."

Input Gate (i_t) and Cell State Candidate ($\hat{C}_t$) – determine what new information will be added to the cell state

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right)$$

$$\tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right)$$

де i_t – input gate, determines which values to update (sigmoid function); $\tilde{C}_t$ – a new candidate for the cell state value (tanh function for generating new values).

Cell State Update (Ct) occurs by combining forgotten old information and adding new information

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

where * denotes element-wise multiplication.

Output Gate (o_t) and Hidden State (h_t) – determine which part of the cell state (C_t) will be output as the hidden state (h_t).

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh(C_t)$$

After the data passes through one or more LSTM layers, the output hidden state (h_t) is fed to a final layer (usually a Dense or linear layer), which transforms it into the final demand forecast ($\hat{y}_t$):

$$\hat{y}_t = W_{out} \cdot h_t + b_{out}$$

where $\hat{y}_t$ – predicted electricity demand at time t; W_{out}, b_{out} – weights and bias of the output layer.

To train the model, a Loss Function is used, which measures the difference between the predicted value ($\hat{y}_t$) and the actual demand (y_t). The most common is the Mean Squared Error (MSE) (often represented via Root Mean Squared Error, RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_t - \hat{y}_t\right)^2}$$

It is often used when large errors are particularly undesirable or costly (which is typical for power systems). A high RMSE compared to MAE indicates the presence of significant, albeit infrequent, forecasting misses.

MAE (Mean Absolute Error) is the arithmetic average of the absolute values of the errors (the difference between the predicted and actual values) for all data points. The MAE value is used by Smart Grid operators to understand the average cost of a planning miss.

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|y_t - \hat{y}_t\right|$$

where N – number of data points; y_t – actual demand at time t; $\hat{y}_t$ – predicted demand at time t.

To evaluate the relative forecasting accuracy, regardless of the absolute load values, the Mean Absolute Percentage Error (MAPE) is also utilized:

$$MAPE = \frac{100\%}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right|$$

Considering that the peak load of the investigated object exceeds 1200 kW, the calculated Mean Absolute Percentage Error (MAPE) is less than 1%. This indicates an exceptionally high accuracy for high-frequency time series, proving that the absolute error margins are negligible relative to the overall system capacity.

The LSTM model serves as an optimal mathematical foundation for implementing the results, as it is specifically designed to analyze dependencies in time series and provides the high accuracy required for critical operations in Smart Grids. The LSTM model provides electricity demand forecasts with high precision for the next few hours or a day (short-term forecasting). Table 1 presents the summarized technical and economic advantages of the LSTM model.

Table 1 – Results of using the LSTM model for demand forecasting in Smart Grids

Expected Result (Quantitative)	Description and Metrics	Practical Value for Smart Grids
High forecasting accuracy	Significant reduction in forecasting error compared to base models (e.g., ARIMA). Metrics: RMSE and MAE are 20–50% lower than traditional methods.	Economic efficiency: Minimization of required operating reserves and reduction of costs in the balancing market.
Successful cycle modeling	Accurate forecasting of daily peaks and troughs, as well as demand fluctuations during the week (weekends vs. weekdays).	Generation planning: Optimal switching on/off of generating capacities and avoidance of network overloads.
Quantitative assessment of weather impact	Identification and utilization of non-linear relationships between external factors (temperature, humidity) and demand.	Proactive management: Precise prediction of demand spikes caused by extreme heat or cold to activate cooling or heating systems.
Efficient processing of high-frequency data	Ability to process data with 5–15 minute discretization, providing a forecast for each interval.	Microgrid management: Rapid decision-making in local systems and precise control of energy storage systems (ESS).
Identification of long-term dependencies	Retention of demand information obtained a week or month ago (via LSTM memory cells).	Forecast stability: Reliability of results even in the event of intermediate anomalies or short-term data failures.
Decision support for ESS	Providing accurate time intervals when energy prices are likely to rise or fall.	ESS optimization: Automation of battery charge/discharge strategies to maximize profit (arbitrage) and support grid frequency.

The study was conducted based on historical demand data with high discretization (5-minute intervals), supplemented by exogenous factors. The main stages of the LSTM model implementation in a machine learning project for time series forecasting are presented in Fig. 1.

The input data provided to the LSTM model for electricity demand forecasting is divided into two main groups:

Primary time series – historical electricity demand (in kW or MW). This is the single variable we aim to predict, as well as a key input feature for the LSTM itself;

Exogenous (external) features – factors that influence demand but are not part of the demand itself (weather data, temporal features, calendar events). These help the model understand the reasons behind changes in demand.

Figure 2, which shows two bar charts (for MAE and RMSE), visually confirms the significant advantage of machine learning and deep learning models over traditional methods for demand forecasting in Smart Grids. The LSTM model (with the shortest bars) demonstrates the highest forecasting accuracy, achieving the lowest values of MAE (7.8 kW) and RMSE (10.5 kW). This indicates its effectiveness in capturing complex, non-linear, and long-term dependencies in high-frequency time series.

The XGBoost model also significantly outperforms the traditional ARIMA model, highlighting the importance of using ensemble methods and the effective use of external features (weather, calendar) in forecasting. The use of LSTM allows for a substantial minimization of operational risks and costs associated with inaccurate forecasting, providing a reliable foundation for energy resource management.

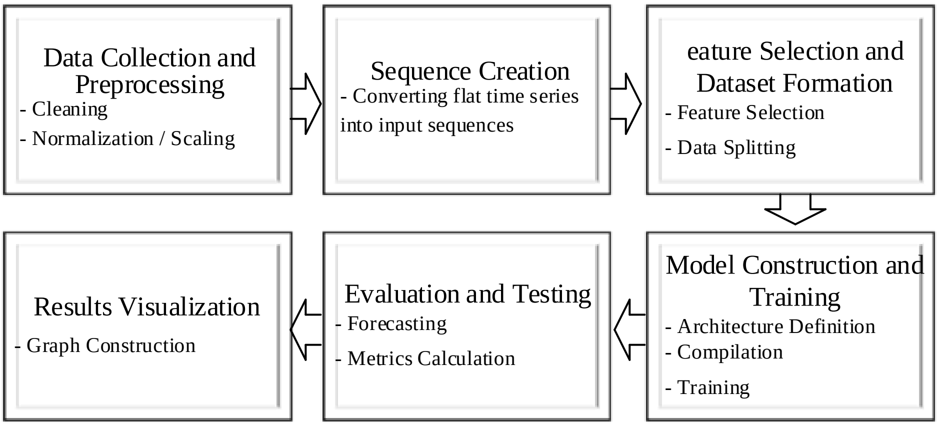
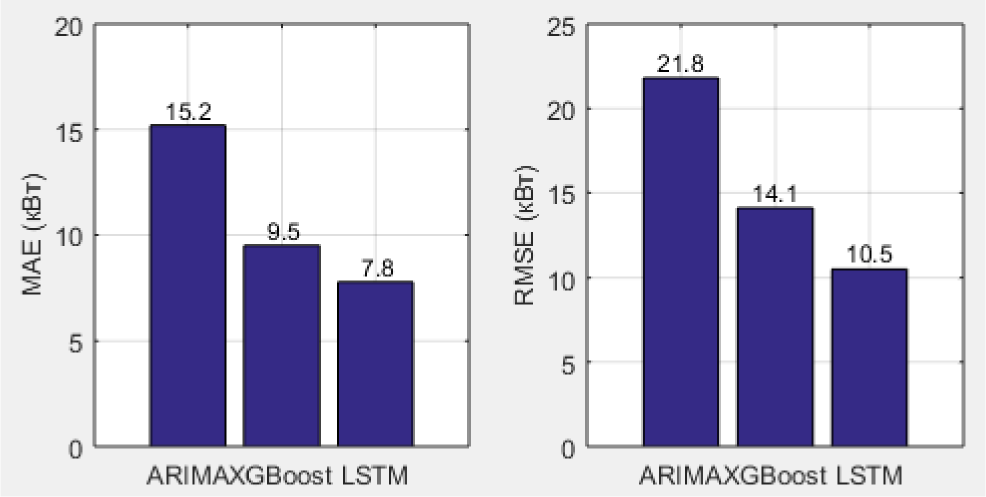


Fig. 1 – Main stages of LSTM model implementation
in a machine learning project for time series forecasting



a b

Fig. 2 – Comparison of MAE values for ARIMA, XGBoost, and LSTM models (a); Comparison of RMSE values for ARIMA, XGBoost, and LSTM models (b)

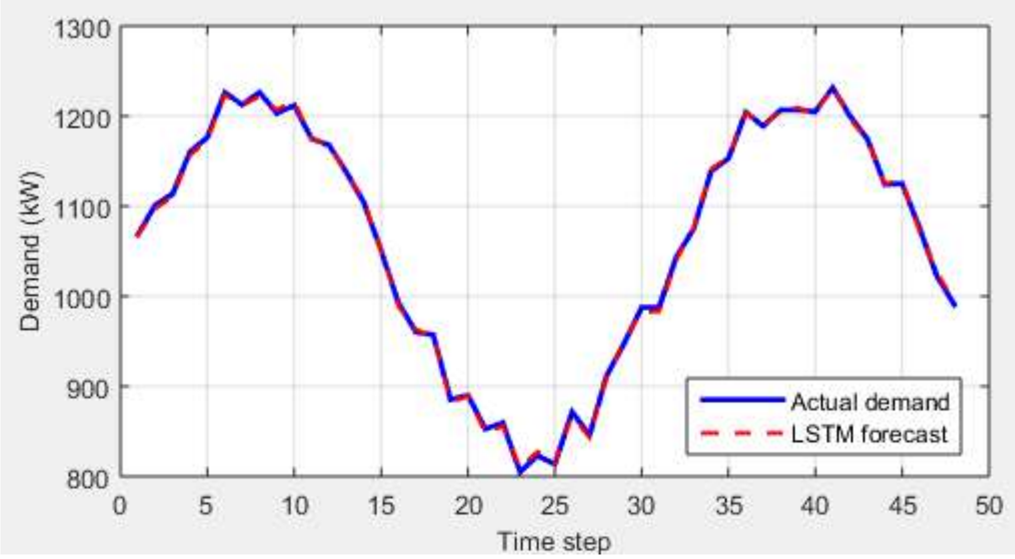


Fig. 3 – Electricity demand forecast

The time series line graph in Fig. 3 is key visual evidence of the model's quality, demonstrating its ability to accurately model demand dynamics. The red dashed line (LSTM forecast) closely overlaps the blue line (actual demand) across all 48 intervals, including periods of fluctuation. Successful dynamics modeling: The model successfully simulates the rises and falls in demand, reflecting its ability to capture the daily cyclicity of consumption. This is critical for operational decision-making (e.g., activating reserve capacities) in Smart Grid environments.

The visual proximity of the lines confirms that LSTM generates reliable short-term forecasts necessary for effective grid balancing.

The residual scatter plot in Fig. 4 provides important information about the nature and distribution of the model's errors. The residual points (errors) are randomly distributed around the zero line (red dashed line), showing no clear patterns, such as constant overestimation or underestimation of the forecast at a specific time of day. This demonstrates the reliability and generalization ability of the LSTM model.

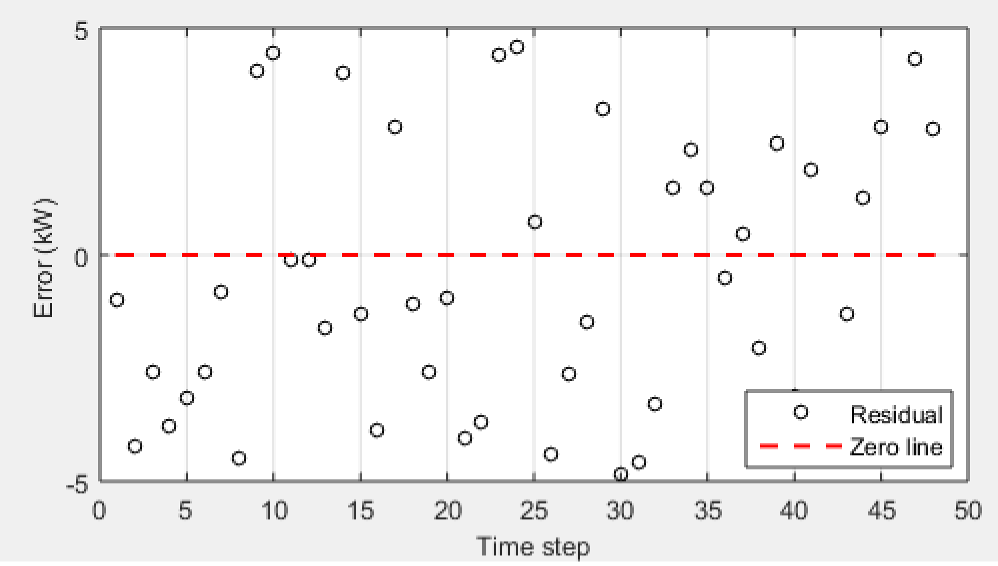


Fig. 4 – LSTM forecast residuals

Most of the points are grouped close to zero, confirming the low MAE value. This means that large errors are rare and non-systematic, which is a sign of high model quality for time series. The uniform distribution of errors indicates that LSTM forecasts can be confidently used for automated grid management.

Conclusion. This study has successfully proven that the configured LSTM model effectively solves the problem of ultra-short-term net demand forecasting using high-frequency data (5-minute intervals), which constitutes the main contribution of this research. LSTM provides a significant reduction in error (by 20-50%) compared to traditional and basic machine learning models. The model successfully captures complex time-series dynamics and lacks systematic errors, making it ideal for automated decision-making.

High-precision forecasts obtained with LSTM directly lead to the minimization of operating costs, optimization of energy storage management, and increased reliability of the entire energy system.

The obtained results and the proposed model architecture can be generalized for the level of microgrids, distribution substations, or multi-apartment complexes. However, at the level of an individual household consumer, the forecasting accuracy may decrease due to the high randomness of switching on specific electrical appliances.

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ПРОГНОЗУВАННЯ ПОПИТУ НА ЕЛЕКТРОЕНЕРГІЮ В SMART GRIDS НА ОСНОВІ МОДЕЛЕЙ МАШИННОГО НАВЧАННЯ

У роботі розглядається актуальна проблема високоточного короткострокового прогнозування попиту на електроенергію в умовах сучасних інтелектуальних енергосистем (Smart Grids). Трансформація енергетичного сектору, зумовлена децентралізацією генерації та масовим впровадженням відновлюваних джерел енергії, потребує нових підходів до обробки великих обсягів високочастотних даних. Обґрунтовано неефективність традиційних статистичних моделей, таких як ARIMA, для аналізу складних нелінійних залежностей у динамічних мережах. Основним методом дослідження обрано модель нейронної мережі Довгої Короткочасної Пам'яті (LSTM), яка дозволяє ефективно вирішувати проблему зникаючого градієнта та вловлювати довготривалі часові залежності. Модель інтегрує як основні часові ряди історичного попиту, так і екзогенні фактори, зокрема погодні умови та календарні події. Експериментальні дослідження проводилися на даних з високою дискретизацією (5-хвилинні інтервали). Результати моделювання продемонстрували значну перевагу LSTM над моделями ARIMA та XGBoost. Використання LSTM дозволило знизити похибки прогнозування (метрики RMSE та MAE) на 20–50% порівняно з традиційними методами, досягнувши значень MAE 7.8 кВт та RMSE 10.5 кВт. Практична цінність отриманих результатів полягає у можливості мінімізації операційних витрат, оптимізації роботи систем накопичення енергії та підвищенні загальної стабільності Smart Grids.

Ключові слова: *енергоефективність, прогнозування попиту, smart grid, машинне авчання, LSTM, рекурентні нейронні мережі.*

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